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EFFECT OF CORRELATIONS AND EQUATION IDENTIFICATION STATUS ON ESTIMATORS OF A SYSTEM OF SIMULTANEOUS EQUATION MODEL

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Abstract: *In simultaneous equations model, multicollinearity and status of identification of the equations have been observed to influence estimation of the model parameters. The error terms of each equation in the model are also expected to be correlated with each other. This study therefore examined the effect of multicollinearity, correlation between error terms and status of identification of equations on six methods of parameter estimation in a simultaneous equations model using Monte Carlo approach. A two equation model, with one equation exactly identified and the other over identified, was considered. The levels of multicollinearity among the exogeneous variables (ρ) and that of correlation between error terms (λ) were considered positive and respectively specified as ρ = 0.3, 0.6, 0.8, 0.9, 0.99 and λ = 0.3, 0.6, 0.9. A Monte Carlo experiment of 250 trials was carried out at three sample sizes (20, 50 and 100). The six estimation methods; Ordinary Least Squares (OLS), Indirect Least Squares (ILS), Limited Information Maximum Likelihood (LIML), Two Stage Least Squares (2SLS), Full Information Maximum Likelihood (FIML) and Three Stage Least Squares (3SLS); were ranked according to their performances. Finite properties of estimators' criteria namely bias, absolute bias, variance and mean squared error were used for comparing the methods. An estimator is best at a specified level of multicollinearity, correlation between error terms and sample size if it has minimum total rank over the model parameters and the criteria. Results show that the OLS estimator is best in estimating the parameters of the exactly identified equation at severe level of multicollinearity ($\rho \to 1$) at all sample sizes. At other levels of multicollinearity, the best estimator is FIML or*

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3SLS except when the correlation between error terms is low (λ = 0.3). At this instance, the best estimators are LIML and 2SLS. The parameters of over identification model are best estimated with FIML or 3SLS at all levels of multicollinearity, correlation between error terms and sample sizes.

***Keywords**: Equation identification status, exactly identified equation, over identified equation, multicollinearity, correlation between error terms, estimators.*

1. Introduction

Simultaneous equations model was developed principally to solve the problem of correlation between explanatory variables and error terms in a single equation model. In this case, the function no longer belongs to a one way causation model but rather a wider system of simultaneous equations (multi-equation model) which describe the relationship among all the relevant variables. The dependent variable Y and independent variables now appear as endogenous variables as well as explanatory variables in other equation (s) of the model. Even with simultaneous equation models, the problem is still inevitable in that individual equations may still exhibit multicollinearity. When the usual techniques of a single equation model are applied, it may lead to an intolerable rise in the size of the model with the consequent depletion of some exogenous variables which may be very needful for the purpose of policy simulation [14].

Apart from this multicollinearity problem, two other problems that are common in econometric models are the problems of equation identification and correlation between the error terms of simultaneous equation model. Identification problem has several common features with multicollinearity. For instance, they both create estimation problems. Thus, identification and absence of strong multicollinearity become very fundamental prerequisites for model parameter estimation but not for theoretical validity of the system of equations. In both cases, there are too many relationships between the variables of the model which do not permit adequate independent variation of the variables. Consequently, some degree of multicollinearity may have to be allowed in the system of simultaneous equations [12]. The problem of correlation between error terms is precipitated on the involvement of more than one equation in the model.

Equation identification of a system of simultaneous equations model becomes very essential in estimation of the model parameters. An equation is either identified or non-identified. If an equation is under identified it is not possible to estimate all its parameters with any of the econometric methods. An equation that is identified is either exactly or over-identified. If an equation is over-identified, it is not possible to obtain unique structural form parameters from the reduced form parameters. However, if an equation is identified it implies that its coefficients can be statistically estimated [12].

There are two basic rules for identification. They are the order condition and the rank condition. The order condition is a necessary but not sufficient condition whereas the rank condition is a sufficient condition. These two rules have been discussed [9, 11, 12].

Several estimators of a system of simultaneous equation model have been given [5, 7, 8, 13, 15]. These estimators include the Ordinary Least Squares (OLS), Indirect Least Squares (ILS), Two Stage Least Squares (2SLS), Limited Information Maximum Likelihood (LIML), Three Stage

Least Squares (3SLS) and Full Information Maximum Likelihood (FIML). These were classified into three approaches namely; the naïve, the limited information and the full information approach [7]. The OLS estimator is the naïve approach. It estimates the parameters of each equation as a single equation. The OLS estimator gives the Best Linear Unbiased Estimates (BLUE) under certain conditions but if the assumptions are weakened the estimates are not BLUE. In the Limited Information (LI) approach, parameter estimation of the whole system of simultaneous equation is just like that of the OLS (one equation is estimated at a time), but unlike OLS it differentiates between explanatory, endogenous variables and included exogenous variables. It does not require information on the specifications of the other equations in the system, especially the identifying restrictions on them. This class includes ILS, 2SLS and K-class estimators like LIML. The Full Information (FI) approach estimates the parameters of the entire system simultaneously using all the information available on each of the equations of the system. 3SLS and FIML belong to this class. The 2SLS and 3SLS are extensions of the OLS while LIML and FIML are extensions of maximum likelihood methods to simultaneous equations estimations. Advantageously, some of these methods of estimation have also been incorporated into some econometric software including the Time Series Process (TSP).

This study therefore examined the effect of multicollinearity (ρ), correlation between the error terms (λ) and equation identification status of the model on the performances of six methods of parameter estimation of a multi-equation model using the Monte Carlo approach.

2. Materials and Methods

A two-equation model of the form:

$$\begin{aligned} &(i)\ y_{1t} = \beta_{12} y_{2t} + \gamma_{11} x_{1t} + \gamma_{12} x_{2t} + u_{1t} \\ &(ii)\ y_{2t} = \gamma_{22} x_{2t} + \gamma_{23} x_{3t} + u_{2t} \end{aligned} \qquad (1)$$

where:

- y_{1t}, y_{2t} = the endogenous variables
- x_{1t}, x_{2t}, x_{3t}= exogenous variables
- u_{1t} and u_{2t} are assumed to be well behaved with a multivariate normal distribution $u_i \sim N(0,1)$, i=1,2.
- β_{12}, γ_{12}, γ_{22}, γ_{23}= the structural parameters of the model, is considered.

Equation (i) is exactly identified while equation (ii) is over identified by both order and rank condition. Equation (ii) does not include an endogenous variable so as to make it over identified. The reduced form of the equations is of the form:

$$\begin{aligned} &(iii)\ y_{1t} = \pi_{11} x_{1t} + \pi_{12} x_{2t} + \pi_{13} x_{3t} + v_{1t} \\ &(iv)\ y_{2t} = \pi_{21} x_{1t} + \pi_{22} x_{2t} + \pi_{23} x_{3t} + v_{2t} \end{aligned} \qquad (2)$$

Thus from Equation (i), the reduced form can be obtained by substituting Equation (ii) into Equation (i). This gives:

$$\begin{aligned} y_{1t} &= \beta_{12}\left(\gamma_{22}x_{2t} + \gamma_{23}x_{3t} + u_{2t}\right) + \gamma_{11}x_{1t} + \gamma_{12}x_{2t} + u_{1t} \\ y_{1t} &= \gamma_{11}x_{1t} + \left(\beta_{12}\gamma_{22} + \gamma_{12}\right)x_{2t} + \beta_{12}\gamma_{23}x_{3t} + \beta_{12}u_{2t} + u_{1t} \end{aligned} \quad (3)$$

Comparing Equation (iii) of (2) with (3):

$$\pi_{11} = \gamma_{11}, \pi_{12} = \beta_{12}\gamma_{22} + \gamma_{12}, \pi_{13} = \beta_{12}\gamma_{23},$$

and

$$v_{1t} = \beta_{12}u_{2t} + u_{1t},$$

Comparing Equation (ii) of (1) with Equation (iv) of (2):

$$\pi_{21} = 0,\ \pi_{22} = \gamma_{22},\ \pi_{23} = \gamma_{23},$$

and

$$v_{2t} = u_{2t},$$

Therefore:

$$\gamma_{11} = \pi_{11} \quad (4)$$

$$\gamma_{23} = \pi_{23} \quad (5)$$

$$\gamma_{22} = \pi_{22} \quad (6)$$

$$\beta_{12} = \frac{\pi_{13}}{\gamma_{23}} = \frac{\pi_{13}}{\pi_{23}} \quad (7)$$

$$\gamma_{12} = \pi_{12} - \beta_{12}\gamma_{22} = \pi_{12} - \frac{\pi_{13}}{\pi_{23}} \cdot \pi_{22} = \pi_{12} - \frac{\pi_{13}\pi_{22}}{\pi_{23}} \quad (8)$$

For the simulation study, the parameters of the model in equation (1) were fixed as β_{12} = 1.5, γ_{11} = 0.5, γ_{12} = 0.8, γ_{22} = 3.0, γ_{23} = 2.3. The levels of multicollinearity among the exogeneous variables (ρ) and that of correlation between error terms (λ) were considered positive and respectively specified as ρ = 0.3, 0.6, 0.8, 0.9, 0.99 and λ= 0.3, 0.6, 0.9. The sample sizes (n) were taken to be 20 (small), 50 (moderate) and 100 (high). The fixed exogeneous variables were generated using the equation provided by Ayinde to generate normally distributed random variables with specified intercorrelations [3]. For three normally distributed random variables, the equations are:

$$\begin{aligned} X_1 &= \mu_1 + \sigma_1 Z_1 \\ X_2 &= \mu_2 + \rho_{12}\sigma_2 Z_1 + \sqrt{m_{22}}\, Z_2 \\ X_3 &= \mu_3 + \rho_{13}\sigma_3 Z_1 + \frac{m_{23}}{\sqrt{m_{22}}} Z_2 + \sqrt{n_{33}}\, Z_3 \end{aligned} \tag{9}$$

where:

$$m_{22} = \sigma_2^2\left[1-\rho_{12}^2\right], m_{23} = \sigma_2\sigma_3\left[\rho_{23}-\rho_{12}\rho_{13}\right], m_{33} = \sigma_3^2\left[1-\rho_{13}^2\right]$$
$$n_{33} = m_{33} - \frac{m_{23}^2}{m_{22}} \quad and \quad Z_i \sim N(0,1) \quad for \quad i = 1,2,3$$

In this study, we assume $X_i \sim N(0,1)$ $\quad for \quad i = 1,2,3$ and the intercorrelations to be the same, i.e. $\rho_{12} = \rho_{13} = \rho_{23} = \rho$. The two stochastic error terms, u_1 and u_2, assumed to be well behaved with a multivariate normal distribution $u \sim NID(0,\Sigma)$ were also generated to exhibit correlation λ using the technique of the equation provided and used by Ayinde and Oyejola [1, 2]. The error terms were thus generated with equation:

$$\begin{aligned} u_1 &= \sigma_1\sqrt{1-\lambda^2}\, z_1 + \sigma_1 \lambda z_2 \\ u_2 &= \sigma_2 z_2 \end{aligned} \tag{10}$$

such that $u_i \sim N(0,1)$ and $z_i \sim N(0,1)$ for i=1,2.
With these specifications, the endogenous variable, y_{1t}, was generated using (3) while that of y_{2t} was generated using (ii) of (1). This Monte-Carlo experiment was performed 250 times (r = 250). For each trial, all the six estimators namely, OLS, ILS, LIML, 2SLS, FIML and 3SLS were used to estimate the parameters of the model. The technique of the ILS method utilized the results of Equations 4-8.
Preferences of estimators were based on bias (closest to zero), minimum absolute bias, minimum variance and minimum mean squared error.
A computer program was written using Time Series Processor (TSP) software to estimate all the model parameters and to evaluate the criteria for each estimator. Based on each estimate of the parameter, the estimators were ranked in order of their performances at each criterion. The evaluation of methods was done at two levels-using individual criterion and the totality of all the four criteria. For the first level, the ranks based on each criterion were added over the parameters of the model for each method. The overall performances of the estimators were examined by further adding the ranks of the first level over the four criteria. An estimator is considered best if it has minimum total ranks. The best estimators are presented in Tables 1, 2, 3, 4, and 5 for the various levels of multicollinearity, correlation between errors and sample sizes for the two types of equations.

3. Results and Discussion

3.1 Performances of the estimators on the basis of bias criterion

From Table 1, for the exactly identified equation, LIML and 2SLS are the best estimators at all levels of multicollinearity and correlation between error terms for small and moderate sample sizes when the bias criterion is used. For large sample sizes, FIML and 3SLS estimators are preferred although the performances of LIML and 2SLS are not much worse. ILS also does fairly well when multicollinearity is high. OLS is not a reliable estimator with respect to bias.

For the over identified equation, the best estimators are FIML and 3SLS when sample size is not large. However, when multicollinearity is very severe ($\rho \to 1$), only 3SLS is good. All the estimators have similar levels of bias when the sample size is large (n= 100) except when multicollinearity is high ($\rho \geq 0.9$). ILS estimator is poor when ($\rho \geq 0.8$). 3SLS is the preferred estimator for the over identified equation under all the conditions considered.

Table 1. Best estimator (s) based on bias criterion

		Equation identification			
		Exactly		Over	
ρ	λ	n ≤ 50	n = 100	n ≤ 50	n = 100
0.3	0.3	LIML 2SLS	FIML	FIML 3SLS	All
	0.6	LIML 2SLS	FIML 3SLS	FIML 3SLS	3SLS
	0.9	LIML 2SLS	FIML 3SLS	FIML 3SLS	All
0.6	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	All
	0.6	LIML 2SLS	FIML 3SLS	FIML 3SLS	All
	0.9	LIML 2SLS	FIML 3SLS	FIML 3SLS	All
0.8	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	All except ILS
	0.6	LIML 2SLS	FIML 3SLS	FIML 3SLS	All except ILS
	0.9	LIML 2SLS	FIML 3SLS	FIML 3SLS	All except ILS
0.9	0.3	3SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.9	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
0.99	0.3	OLS ILS	ILS FIML	ILS 3SLS	
	0.6	ILS LIML 2SLS	OLS LIML 2SLS	3SLS	3SLS
	0.9	OLS	ILS LIML 2SLS	3SLS	3SLS

3.2 Performances of the estimators on the basis of absolute bias criterion

Table 2 gives the summary of the performances of the estimators on the basis of absolute bias criterion.

For the exactly identified equation, LIML and 2SLS estimators are best except for high level of correlation between error terms or for large sample sizes when FIML and 3SLS estimators are preferred. However, when both the level of multicollinearity and correlation between the error terms are high, OLS estimator is preferred.

For the over identified equation, the best estimators are FIML and 3SLS. However, when sample size is small and multicollinearity level is high ($\rho \geq 0.8$), OLS is best. The performances of the other estimators are similar but are not as good as FIML or 3SLS. ILS is consistently a poor estimator.

Table 2. Best estimator (s) based on absolute bias criterion

		Equation identification			
		Exactly		Over	
ρ	λ	n ≤ 50	n = 100	n ≤ 50	n = 100
0.3	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	LIML 2SLS FIML	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.9	FIML 3SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
0.6	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.9	FIML 3SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
0.8	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.9	FIML 3SLS	FIML 3SLS	LIML 2SLS 3SLS	FIML 3SLS
0.9	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	LIML 2SLS 3SLS	FIML 3SLS	LIML 2SLS	FIML 3SLS
	0.9	FIML 3SLS	FIML 3SLS	LIML2SLS 3SLS	FIML 3SLS
0.99	0.3	FIML OLS ILS	OLS	FIML/3SLS	3SLS
	0.6	OLS	OLS	FIML/3SLS	3SLS
	0.9	OLS	OLS	3SLS	3SLS

3.3 Performances of the estimators on the basis of variance criterion

Table 3 gives the summary of the best estimators based on the variance criterion. For the exactly identified equation, FIML and 3SLS estimators have least variances irrespective of sample size, except when multicollinearity is high. Even then, FIML is still a good estimator. When multicollinearity is severe ($\rho \rightarrow 1$), the best estimators are OLS and FIML. FIML therefore appears to be a good estimator in terms of low variance for the exactly identified equations under various levels of multicollinearity and correlation between error terms.

For the over identified equation, all the methods except ILS perform well when multicolinearity is not high ($\rho \geq 0.6$). However, when multicollinearity is high, FIML or 3SLS estimators are preferred though at very high multicollinearity ($\rho \rightarrow 1$) and at least moderate sample size, 3SLS is preferred.

Table 3. Best estimator (s) based on variance

		Equation identification			
		Exactly		Over	
ρ	λ	n ≤ 50	n = 100	n ≤ 50	n = 100
0.3	0.3	FIML 3SLS	FIML 3SLS	FIML 3SLS	All except ILS
	0.6	FIML 3SLS	FIML 3SLS	FIML 3SLS	3SLS
	0.9	FIML 3SLS	FIML 3SLS	FIML 3SLS	All except ILS
0.6	0.3	FIML 3SLS	FIML 3SLS	FIML 3SLS	All except ILS
	0.6	FIML 3SLS	FIML 3SLS	FIML 3SLS	All except ILS
	0.9	FIML 3SLS	FIML 3SLS	All except ILS	All except ILS
0.8	0.3	LIML 2SLS 3SLS	FIML 3SLS	All except ILS	FIML 3SLS
	0.6	FIML 3SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.9	FIML 3SLS	FIML 3SLS	All except ILS	FIML 3SLS
0.9	0.3	FIML	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	FIML/3SLS	FIML 3SLS	OLS LIML 2SLS 3SLS	FIML 3SLS
	0.9	FIML/3SLS	FIML 3SLS	OLS LIML 2SLS 3SLS	FIML 3SLS
0.99	0.3	OLS FIML	OLS FIML	All except ILS	3SLS
	0.6	OLS FIML	OLS FIML	All except ILS	3SLS
	0.9	OLS FIML	OLS FIML	All except ILS	3SLS

3.4 Performances of the estimators on the basis of mean square error criterion

Table 4 gives the summary of the performances of the estimators at the various levels of multicollinearity, correlation between the error terms and sample on the basis of mean square error criterion. The OLS estimator is best though FIML competes well with it. When correlation between error terms is low (λ<0.6) and multicollinearity is not severe then LIML and 2SLS are the best.

For the over identified equation, all the estimators except ILS perform well. ILS had high mean square errors. However, FIML and 3SLS performed better at high levels of multicollinearity and correlation between error terms. Generally, 3SLS is the preferred estimator.

Table 4. Best estimator (s) based on mean square error

		Equation identification			
		Exactly		Over	
ρ	λ	n ≤ 50	n = 100	n ≤ 50	n = 100
0.3	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	All except ILS
	0.6	FIML 3SLS	FIML 3SLS	FIML 3SLS	All except ILS
	0.9	FIML 3SLS	FIML 3SLS	FIML 3SLS	All except ILS
0.6	0.3	LIML 2SLS	FIML 3SLS	All except ILS	All except ILS
	0.6	FIML 3SLS	FIML 3SLS	All except ILS	All except ILS
	0.9	FIML 3SLS	FIML 3SLS	All except ILS	All except ILS
0.8	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	FIML 3SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.9	FIML 3SLS	FIML 3SLS	FIML 3SLS	3SLS
0.9	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	LIML 2SLS FIML	FIML 3SLS	3SLS FIML	3SLS
	0.9	FIML 3SLS	FIML 3SLS	3SLS	FIML 3SLS
0.99	0.3	OLS	OLS FIML	All except ILS	3SLS
	0.6	OLS	OLS FIML	FIML/3SLS	3SLS
	0.9	OLS FIML	OLS FIML	OLS LIML 2SLS 3SLS	3SLS

3.5 Overall performances of the estimators on the basis of all the criteria

Table 5 reveals that for estimating the parameters of exactly identified equation, the LIML and 2SLS are the best estimators when multicollinearity is not severe ($\rho \leq 0.9$) and sample size is not large. When sample size is large, FIML and 3SLS are the best. OLS is preferred when multicollinearity is high.

For the over identified equation, 3SLS is always one of the best estimators. Sometimes FIML is also good.

Table 5. Best estimator (s) based on all criteria

		Equation identification			
		Exactly		Over	
ρ	λ	n ≤ 50	n = 100	n ≤ 50	n = 100
0.3	0.3	LIML 2SLS FIML	FIML	FIML 3SLS	FIML 3SLS
	0.6	FIML 3SLS	FIML 3SLS	3SLS	3SLS
	0.9	FIML 3SLS	FIML 3SLS	FIML 3SLS	3SLS
0.6	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	3SLS
	0.6	FIML	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.9	FIML 3SLS	FIML 3SLS	FIML 3SLS	3SLS
0.8	0.3	LIML 2SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.6	FIML 3SLS	FIML 3SLS	FIML 3SLS	FIML 3SLS
	0.9	FIML 3SLS	FIML 3SLS	3SLS FIML	3SLS
0.9	0.3	LIML 2SLS	FIML 3SLS	3SLS FIML	3SLS
	0.6	LIML 2SLS	FIML 3SLS	3SLS FIML	3SLS
	0.9	LIML 2SLS	FIML 3SLS	3SLS FIML	3SLS
0.99	0.3	OLS	OLS FIML	3SLS	3SLS
	0.6	OLS	OLS	3SLS	3SLS
	0.9	OLS	OLS	3SLS	3SLS

4. Conclusions

In this study, we have examined the performances of the six estimators in estimating parameters of the structural equations. Criteria considered are bias, absolute bias, variance and mean square error. In recommending appropriate estimators, we have considered mainly bias and mean square error of the estimators.

FIML and 3SLS but particularly 3SLS were observed to be the appropriate methods of estimation of the parameters of the over identified equations at all levels of positive correlation between errors and multicollinearity and sample sizes.

FIML and 3SLS are also the best estimators of the structural equations of the exactly identified equations when the sample size is large except when multicollinearity is severe. OLS is a better estimator when multicollinearity is severe for whatever sample size. A similar result from various studies with respect to performance of OLS in the presence of multicollinearity has been reported [12]. When the sample size is small and multicollinearity is not severe, LIML or 2SLS are the best estimators for estimating the structural parameters of the exactly identified equations. Further study is being carried out to compare these results with the results in the presence of negative correlations.

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